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Unit labour costs and manufacturing returns

An analysis of a relationship in Northern Europe

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Abstract

I use quarterly data from the most recent 19 years to assess the existence of two hypothetical effects: a relationship between unit labour cost changes and manufacturing returns, and an effect, where offshoring firms produce higher returns than domestic counterparts. I construct a simple linear regression model using OLS estimation, and compare manufacturing results with a control group of finance returns, both analysed with the same model. The results are mixed: unit labour costs affect both samples' returns inversely and significantly, but the finance sample's results are weaker. In light of the results, I argue, that unit labour cost variations affect manufacturing returns particularly strongly. The second hypothesis of higher returns for offshoring firms cannot be confirmed: the results give indications of the effect, but aren't significant.

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1. Introduction

1.1. Research Question and Contribution

There have been several instances in recent Finnish history, where factories have been closed with great publicity, most recently, UPM’s Kaipola paper mill in Jämsä. As has often been the case, high labour costs of Finland were cited as one reason for the closure (UPM, 2020). The primary aim of listed companies tends to be to maximise shareholders’ wealth, and the decisions the management makes should logically reflect this aim. The research question of this paper is therefore twofold: do unit labour cost variations have a statistically significant relationship with manufacturing stock returns, and do manufacturing companies, that produce a significant amount of their goods in lower labour cost countries, experience higher returns than primarily domestic firms?

The possible relationship of unit labour costs with stock returns hasn’t been widely researched, and the availability of historic ULC data from a wide variety of countries, thanks to organisations such as the OECD, gives rise to an interesting angle for research. This paper provides an analysis of the relationship between unit labour costs and manufacturing returns in a quarterly sample of three countries, Finland, Sweden and Germany, from the time period March 2001 to December 2019. To assess the results of the manufacturing analysis, comparable finance returns are analysed using the same model.

The results of the analysis show, that unit labour costs have a significant, inverse relationship with manufacturing returns in the sample period. The same effect can be found, as weaker, in the finance data as well. Taking model fit and regression-wide significance into account, I argue, that unit labour costs explain manufacturing returns particularly well. The second question of offshoring firms outperforming domestic ones cannot be answered conclusively: although offshoring is very common in the sample, the effect of it providing higher returns cannot be shown to be significant in the sample data.

1.2. Literature Review

OECD (2008) defines unit labour costs [referred to as ULCs in this paper] as a measure of the “average cost of labour per unit of output”. The organisation calculates its numbers, which are used in this paper, as the ratio of mean labour costs to labour productivity. These components are affected by many macroeconomic variables, such as labour agreements, technology level and capital intensity. The measure "represents a link between productivity and the cost of labour in producing output".

Unit labour cost, per its components, varies according to many conditions. Casey (2012), examining Irish ULCs, notes that Ireland is heavily dependent on exports, which is why competitiveness, and ULCs are a "key variable" to take into account. This same export-dependency applies to Finland, and is often referred to in Finnish public discourse (e.g. Ilta-Sanomat, 2014). Casey remarks, that an Irish ULC decline in the early 2010's "is indicative of labour productivity growth outstripping that of average compensation levels for employees, thus lowering costs faced by producers and providing an increasingly more favourable labour environment". This summarises some of the possible factors that affect ULCs year-by-year.

While productivity and labour costs are relatively comparable between Eurozone countries, there have been noticeable differences in ULC developments during the 2000's. Ordóñez et al. (2015) discuss differences between selected Eurozone countries' real unit labour costs. They argue that southern European countries such as Italy and Spain have succeeded better in reducing their RULCs than their northern counterparts. However, their technological progress has been relatively weak during the observation period. All countries in their sample have experienced falls in RULCs, but the lowest falls have been experienced by Finland and Belgium. The authors assess the disparity to be "the outcome of a less expansionary wage growth process mainly counterbalanced through capital intensity gains."

The results of Ordóñez et al. (2015) imply that there has been growing divergence in unit labour costs within the Eurozone, which some suggest might be linked to the common currency. Pancotto & Pericoli (2014, cited by Ordóñez et al. 2015) find that "the introduction of the Euro has increased -- the distance among member countries, as measured in the metric of unit labour costs". However, further research in their paper suggests that this phenomenon could be "driven by real factors, i.e. diverging technological patterns –". Both trends are particularly strong in the manufacturing industry. Pancotto & Pericoli add, that their results are similar to previous research from Fischer (2007), who suggests a "pattern of loss of competitiveness" of other Eurozone countries compared to Germany. In any case, there seems to be significant differences between ULC developments in different European countries despite their interconnectedness, and the monetary union might play a part.

Espinosa & Sánchez (2016) link favourable German export performance in the early 2000's with some components of the ULC measure. They find, that German exports were "positively related to the development of unit labour costs primarily through the productivity performance and not via the evolution of wages”. They find this effect mostly through the high tech industry part of their sample, while the effect on “low technology” firms is not very significant. This makes sense intuitively, since productivity increases in high tech industries might be more impactful and common when compared the industries with a lower level of technology. This effect is somewhat contradictory to the hypotheses presented in this paper.

As noted, productivity is one of the ULC components, and its developments have large impacts on ULCs. Bakhtiari (2015) discusses the relationship between productivity and outsourcing. They write that “productivity is the principal determinant of outsourcing and that low productivity should significantly raise the likelihood of the outsourcing decision.” In their paper they also refer to previous literature such as Tomiura’s 2007 paper (cited in Bakhtiari 2015), where an effect is found within Japanese firms, where “productivity of firms sourcing offshore tends to be higher than that of firms sourcing only within their home country”. Fariñas & Martin-Marcos (2010, cited in Bakhtiari 2015) have also studied the effect within the Spanish manufacturing sector, with similar results. They summarise their findings by saying that “the productivity advantage is highest for firms that import inputs from foreign subsidiaries”. Several academics seem to agree that offshoring and outsourcing decisions improve productivity. Productivity increases, by definition, decrease ULCs, and could also logically reflect in higher stock returns following increased firm competitiveness.

Implicitly, higher productivity could indeed lead to higher aggregate stock returns through improved firm performance. However, research by Chun et al. (2016), shows, that firms are not only affected by their own productivity growth, but also by the productivity growth rates of other firms. Stock returns and productivity are correlated positively on firm-level, but negatively on aggregate-level in their sample. They attribute this fact to creative destruction: if one firm gains a large competitive advantage, this will impact the business of other firms negatively. They conclude that “while some firms’ shares do rise with aggregate [Total Factor Productivity] growth, most firms’ shares drop”. If ULC falls that are caused by increased aggregate productivity, indicate poor returns, this could be a viable explanation.

2. Data and Methodology

2.1. Returns Data

The method chosen to research the hypotheses is a simple linear regression using the OLS estimation method. In the regression, a sample of stock returns is regressed on ULC data and several control variables to isolate the relationship between ULCs and stock returns. To assess the nature of the effects further, the same regression is performed with a sample of finance returns from the same countries, from the same period of time. To assess the second hypothesis, a dummy variable is introduced to signify primarily domestic-operating companies.

I gather two samples of stocks, and their quarterly returns, from March 2001 to December 2019. The first sample contains quarterly returns from 129 Finnish, Swedish and German manufacturing companies, while the second contains returns from 87 financial firms from the same countries, as a control group. These returns are regressed on ULC data, gathered from the OECD database, while controlling for several, both firm- and country-specific variables.

The companies in the manufacturing sample are further divided into two groups, according to whether they manufacture the clear majority of their products in their home country. The data was gathered by going through information about each company's production facilities, mostly from their websites. A dummy variable of 1 is assigned for the companies that fulfil the criterion, while a dummy variable of 0 signifies the companies which have moved significant production outside their home countries. In total, the manufacturing sample consists of 27 Finnish, 50 Swedish and 52 German firms (=129). 7 Finnish, 17 Swedish and 18 German firms (=42) fulfil the dummy condition. The dummy coefficient will explain, whether companies with diversified production locations significantly outperform those companies that only manufacture in their home country – negative dummy values would signify outperformance.

The second sample consists of financial companies from the same three countries. In total, there are 13 Finnish, 59 Swedish and 15 German firms (=87). Since manufacturing is an industry quite reliant on labour, a sample of a less labour-reliant industry helps to understand the results. In other words, the finance sample acts as a control group, to signify whether the ULC variations have a larger impact on manufacturing returns, compared to other industries.

Three clear outlier return variables are deleted from the finance data, and one from the manufacturing data. Each of these outliers is at least twice as high as the next highest variable, and clearly stands out from the rest of the samples. These outliers are unlikely to have occurred due to unit labour cost variations, and to avoid distortion of the results and heteroscedasticity, they are deleted from the sample.

Presented below are some relevant statistics about the stocks in the sample and their returns. In total there are 216 companies in the sample, with data from 76 quarters from March 2001 through to December 2019. Manufacturers that have diversified their production into several countries seem to enjoy higher mean and median returns than localised firms in the sample period. The standard deviations are quite comparable, which is no surprise seeing that the firms operate in the same industry. The finance statistics are very similar with the diversified manufacturing statistics.

The country-level statistics provide additional insight to the sample. Both Swedish manufacturing and finance industries have outperformed Finnish and German industries in the 2000's. The Swedish sample subsets also have very similar mean and median returns with each other. The German finance industry has fared the worst of the sample subsets, with the lowest returns by far. The manufacturing sample is relatively well balanced in terms of observations per country, but in the finance sample's Swedish companies are somewhat overrepresented. This means, that Swedish results will drive the sample-wide finance results in large part.

Table 1: Sample statistics per industry type.

	Manufacturers, Local	**Manufacturers, Offshoring**	**Financial**
No. of Unique Firms	42	87	87
No. of Observations	3192	6612	6612
Mean	3.383	3.812	3.719
Median	1.553	3.067	3.059
Standard Deviation	23.553	20.192	17.913

Table 2: Sample statistics per country and industry.

	Manuf. FIN	**Fin. FIN**	**Manuf. SWE**	**Fin. SWE**	**Manuf. GER**	**Fin. GER**
No. of Unique Firms	27	13	50	59	52	15
No. of Observations	2052	988	3800	4484	3952	1140
Mean	2.831	3.497	4.262	4.275	3.622	1.363
Median	1.664	1.963	2.941	3.788	2.731	1.081
Standard Deviation	20.690	18.921	20.758	16.661	22.418	21.844

2.2. Unit Labour Cost Data

The primary explanatory data, the unit labour cost percentage changes, is collected from the OECD database (OECD, 2020). The data is quarterly and country-specific – other data is computed to fit the quarterly frequency. The ULC percentage changes are sourced primarily from the OECD National Accounts Statistics database.

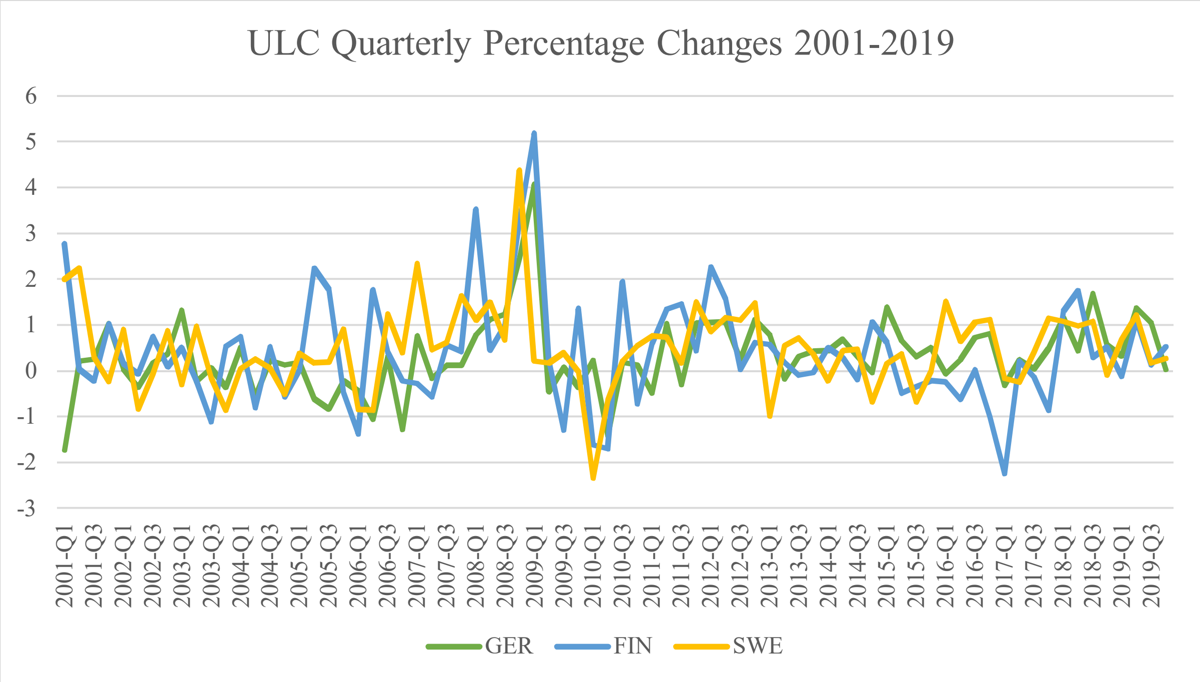
Table 3: Correlation matrix of the ULC data.

	FIN	SWE	GER
FIN		0.288	0.403
SWE	0.288		0.297
GER	0.403	0.297	

Table 4: Sample statistics of the ULC data.

	FIN	SWE	GER
Mean	0.409	0.487	0.334
Median	0.249	0.406	0.248
St. Dev.	1.196	0.908	0.825

Figure 1: ULC variations charted.



Above are some descriptive statistics of the ULC data. The means are relatively comparable but also have many differences, with Sweden having had the highest mean ULC growth, and Germany the lowest. The Swedish median is also the highest, while Finland has had the most volatile ULCs during the 2000's. The chart illustrates the ULC variations, with especially the Financial Crisis standing out with a spike across the countries, followed by a fall in the ULCs. Overall, all means and medians are clearly positive, meaning that the ULCs have crept upwards during the 2000's. Inflation, of course, plays a part in this effect, especially taking into account the research by Ordóñez, et al. (2015) which shows that real unit labour costs have fallen in Eurozone countries.

The correlation matrix describes the Pearson correlation coefficients between the ULC variations of the countries in the sample. Finnish and German ULCs stand out as the most correlated. The most notable correlations between the countries have most likely has to do with macroeconomic events that affect the entire world economy, such as the Financial Crisis, which can be seen as a spike in each country's data in 2008. Interestingly, Finland and Germany experience the spike one quarter later than Sweden – signifying that the shock arrived later into these countries. The correlation coefficients, however, are relatively small, and there seem to also be significant domestic factors driving the ULCs. As Ordoñez et al. (2015) and Pancotto & Pericoli (2014) suggest, there are notable differences between each countries ULCs, i.e.

competitiveness developments, despite all belonging to the EU single market and sharing many common regulations.

2.3. Control Variables and Complete Model

To gather reliable results and isolate the actual effects of the ULCs, control variables are needed. Included in the analysis are stock-specific Betas, Net Profit Margins and Book-to-Market ratios from the entire sample period, gathered from the Refinitiv Eikon and Datastream databases. In addition, the previously mentioned dummy variable is present in the manufacturing regression,

As a macro variable, the corresponding return of the local market index is included for each country. In addition, the Fama-French three-factor-model (Fama & French, 1992) factors of SMB (small-minus-big) and HML (high-minus-low) are included to explain the returns further, and isolate the effects we are interested in. The Fama-French factors are gathered from the Kenneth R. French data library's European data, and the monthly data is computed to reflect quarterly returns.

Written out, the model reads as:

$$Return = \alpha + \beta * ULC + \gamma * Dummy + \delta * Beta + \varepsilon * Market\ return$$
$$+ \epsilon * SMB + \theta * HML + \vartheta * Book\ to\ market + \mu * Net\ profit\ margin$$

The finance regressions, of course, lack the dummy variable.

3. Results

3.1. Sample-wide results

In the beginning, I conduct two regressions, with the whole manufacturing and finance samples. These regressions gauge general results on a wide scale with a large sample size, and provide the main results. To follow up and assess country-specific results and country-level similarities and differences, I conduct six regressions on country and industry level. Robustness checks follow after the results.

The two hypotheses in the research question are tested. Hypothesis 1: Unit Labour Costs have a negative relationship with manufacturing stock returns with a 95 % confidence interval, i.e. the ULC estimates will be negative and significant. Hypothesis 2: Manufacturers that have production in several countries outperform manufacturers with predominant production in their home countries, i.e. the dummy variable has a negative and significant (>95 %) coefficient. These hypotheses are mainly tested on the level of the whole sample, while the country-level results provide additional insight.

Table 5: Regression results across the sample. The main values are T-statistics, with P-values in parentheses. Regression statistics presented at the bottom.

Variable	Manufacturing	Finance
(Intercept)	3.169 (0.000)	4.102 (0.000)
ULC	-1.250 (0.000)	-1.061 (0.001)
Dummy	-0.271 (0.565)	-
Beta	-0.255 (0.502)	-0.753 (0.056)
Market	0.859 (0.000)	0.861 (0.000)
SMB	3.532 (0.000)	1.747 (0.000)
HML	-1.791 (0.000)	0.430 (0.021)
BM	-0.008 (0.008)	0.000 (0.192)
Profit	0.003 (0.004)	0.000 (0.984)

Adjusted R-squared	0.2256	0.1393
F-statistic	261.1	81.19
N	129	87

In these regressions we get a general picture of the results. The main variable of interest, ULC, has a very significantly negative coefficient in the manufacturing regression, while the ULC coefficient for the finance returns is negative and significant as well. The dummy variable present in the manufacturing regression is negative, but it is not significant.

From the R-squared statistic it can be seen, that the model explains manufacturing returns well, but does not fit quite as well for the finance returns. The F-statistic is also far higher for the manufacturing regression, signifying more reliable results. This is to be expected, since the model and the variables have been built with the manufacturing industry in mind.

3.2. Country- and Industry-specific Results

Table 6: Finnish results.

Variable	**Manufacturing**	**Finance**
(Intercept)	2.971 (0.003)	-2.035 (0.278)
ULC	-0.490 (0.223)	-0.651 (0.381)
Dummy	-0.720 (0.498)	-
Beta	0.216 (0.814)	9.544 (0.000)
Market	0.698 (0.000)	0.719 (0.000)
SMB	2.951 (0.000)	0.660 (0.338)
HML	1.862 (0.000)	1.131 (0.049)
BM	-0.121 (0.054)	0.000 (0.846)
Profit	-0.002 (0.314)	-0.230 (0.138)
Adjusted R-squared	0.242	0.215
F-statistic	66.27	19.71
N	27	13

Table 7: Swedish results.

Variable	**Manufacturing**	**Finance**
(Intercept)	5.653 (0.000)	6.930 (0.000)
ULC	-2.434 (0.000)	-2.081 (0.000)
Dummy	-0.118 (0.883)	-
Beta	-0.092 (0.884)	-2.351 (0.000)
Market	1.270 (0.000)	0.949 (0.000)
SMB	2.828 (0.000)	1.588 (0.000)
HML	0.588 (0.023)	0.500 (0.020)
BM	-0.034 (0.006)	0.000 (0.384)
Profit	0.005 (0.000)	-0.003 (0.574)
Adjusted R-squared	0.100	0.0833
F-statistic	38.42	32.46
N	50	59

Table 8: German results.

Variable	**Manufacturing**	**Finance**
(Intercept)	1.344 (0.069)	-0.382 (0.738)
ULC	-1.144 (0.009)	1.674 (0.079)
Dummy	-0.375 (0.595)	-
Beta	0.167 (0.774)	-0.134 (0.795)
Market	1.006 (0.000)	1.095 (0.000)
SMB	4.202 (0.000)	2.808 (0.000)
HML	-0.054 (0.823)	-0.309 (0.543)
BM	-0.007 (0.040)	0.006 (0.000)
Profit	0.096 (0.000)	-0.017 (0.000)
Adjusted R-squared	0.3291	0.3517
F-statistic	173.9	42.46
N	52	15

The Finnish subset of the sample produces negative coefficients for the ULC and dummy variables, but it fails in producing any significant estimates. This might have something to do with the low sample sizes. The R-squared and F-statistic numbers tell that the model fits well for manufacturing, while the finance industry has slightly lower numbers.

The Swedish samples provide the most significant P-values out of the countries, for both industries. The ULC coefficients are also the lowest. However, the model also fits the worst for the Swedish countries, with the lowest R-squared factors. The Swedish finance results drive the sample-wide finance results quite heavily, since more than half of the finance sample stocks are listed in Sweden.

Lastly, the German results provide the best fits for the model. The ULC coefficient for the manufacturing industry is significant, and the model fits well. The German finance results provide an insignificant and the only positive ULC coefficient. Analysis of the results follows in the discussion section.

3.3. Robustness Checks

To assess the reliability and robustness of the results, I perform tests for autocorrelation and heteroscedasticity on the main regressions. The Breusch-Godfrey test for autocorrelation provides extremely small P-values (< 2.2e-16) for both regressions, confirming that autocorrelation isn't an issue in the data. The Breusch-Pagan test for heteroscedasticity produces a very small P-value for the manufacturing sample, and a P-value of 0.005 for the finance sample. Therefore it can be said, that neither sample suffers from autocorrelation nor heteroscedasticity.

To further assess the results' robustness, I construct heteroscedasticity- and autocorrelation-consistent standard errors and T-statistics. The largest changes in the main sample between the original and the robust values are with the Net Profit Margin and Alpha values. The variables we are mainly interested in, ULC and Dummy, remain quite similar to the original values. As the ULC variable also remains significant, the results confirm, that a relationship between ULCs and manufacturing returns is robust within the regression.

Table 9: Robust T statistics and standard errors for the main sample.

Variable	Estimate	St. Error	T Stat	Rob. SE	Rob. T St.
(Intercept)	3.169	0.465	6.809	0.549	5.774
ULC	-1.250	0.242	-5.174	0.254	-4.929
Dummy	-0.271	0.470	-0.575	0.500	-0.542
Beta	-0.255	0.380	-0.672	0.529	-0.482
Market	0.859	0.024	35.642	0.026	33.139
SMB	3.532	0.203	17.356	0.212	16.694
HML	-1.791	0.162	-11.079	0.124	-14.467
BM	-0.008	0.003	-2.641	0.004	-2.330
Profit	0.003	0.001	2.844	0.002	1.405

The finance sample's robust coefficients do not diverge particularly heavily from the original values either. The ULC value remains significant, while the biggest changes occur in the Market and Beta values. The finance results seem to be robust as well.

Table 10: Robust T statistics and standard errors for the finance sample.

Variable	Estimate	St. Error	T Stat	Rob. SE	Rob. T St.
(Intercept)	4.102	0.507	8.089	0.569	7.211
ULC	-1.061	0.333	-3.190	0.347	-3.059
Beta	-0.753	0.394	-1.912	0.628	-1.199
Market	0.861	0.041	21.123	0.046	18.884
SMB	1.747	0.268	6.527	0.279	6.268
HML	0.430	0.187	2.304	0.229	1.876
BM	0.000	0.000	1.306	0.000	1.711
Profit	0.000	0.005	-0.020	0.004	-0.021

Another method of testing the significance of the results is the F test. It provides a value well over the critical limit for the manufacturing regression – meaning that the null-hypothesis of no relationship between ULCs and manufacturing returns can be rejected. The F test for the manufacturing sample produces a value of 36.752, well over the critical level of 3.842. In the case of the finance sample, the F test produces a value of 19.414, also with a critical level of 3.842. Both results are clearly significant, but the difference between the manufacturing and finance regressions can be seen in these statistics.

4. Discussion

4.1. General Interpretation

The results of the main sample suggest that the first hypothesis of a relationship between unit labour costs and manufacturing returns exists within the sample. The ULC coefficient is negative, as hypothesised, which implies an inverse correlation between ULCs and returns – i.e. when ULCs go down, returns go up. The coefficient is comfortably significant on a 95 % confidence level, also reaching 99 %. The sample does not suffer from autocorrelation nor heteroscedasticity, and the robust standard errors and T statistics maintain the significance of the results. In light of the results, unit labour cost variations do explain manufacturing returns significantly, and the first hypothesis can be confirmed.

However, the control group of the finance returns casts some doubt on a particularly strong relationship between the ULC variations and manufacturing returns. The ULCs, most likely driven by the macroeconomic factors behind the measure, also have a significant impact on the finance returns. Still, while both main ULC coefficients are significant, the overall data shows a lower (more negative, i.e. a stronger factor) coefficient for manufacturing than finance. Further country-level analysis shows, that every significant manufacturing ULC coefficient is lower than the corresponding finance ULC coefficient, but quite narrowly. The German data shows the clearest difference between the two industries: the ULC coefficient is far lower for manufacturing than finance.

Thus, upon analysing the results closely, I argue, that the ULCs do explain manufacturing returns better than other industries in the sample-wide results. The differences between ULC coefficients are small between the two industries, but further insight can be drawn from model fit and model-wide regression significance. The R-squared is far higher for the main manufacturing sample than the finance sample. In addition, the F-statistics are much higher in the manufacturing regressions, both the sample-wide and country-level ones.

The measure of unit labour cost reflects its components, which are productivity and costs per employee. Productivity is a widely researched and complex factor, which, for example, the OECD (2001, p. 11) defines as "a ratio of a volume measure of output to a volume measure of input use". Factors such as technology level and efficiency play a large part in defining productivity level. Chun et al.'s 2016 result of aggregate production gains lowering aggregate returns does not seem to show in this regression. Productivity increases would decrease ULCs, which, this paper's model suggests, increases returns. Of course, the effect might be underlying, since productivity is only one ULC component. The German competitiveness advantage noted by Fischer (2007) does not seem to affect the results either – however, this effect seems to be visible in Germany having the lowest ULC rises in the sample period.

The other component, costs per employee, is also affected by many variables, from collective labour agreements to, again, available technology. The rationale for a strong ULC-manufacturing relationship, and causality of the results, is clear: industries more reliant on labour, such as manufacturing, could be more likely to see their returns vary with costs per employee – and therefore unit labour costs. The results point towards this being the case. There are many macroeconomic variables affecting labour costs, many of which, admittedly, could also affect company performance and therefore returns directly. The results of the model are quite appropriate in their relative ambiguity, but this ULC-focused model does indeed explain manufacturing returns better than finance returns.

The second hypothesis of lower returns for domestic firms (dummy variable 1) cannot be confirmed by the results. While the coefficients for the dummy variable are consistently negative throughout the sample, indicating, that domestic firms would produce lower returns, they aren't particularly close to being significant. As discussed in the literature review, academics have found an effect, where outsourcing and offshoring improves the productivity of a company and, logically, higher returns should follow. The results of this paper point to the direction that the effect could exist within the sample countries – but it isn't significant within this relatively narrow sample. A larger sample could help in finding a significant effect, and one could possibly be found on a European level.

Previous literature makes a compelling case for the existence of such an effect. As considered in the literature review, many researchers, such as Fariñas et al. (2010), Bakhtiari (2015) and Tomiura (2007), have found a factor where offshoring and outsourcing production improves productivity within the firm. The literature focuses on productivity, but it is possible, that productivity gains would reflect in higher stock returns as well. Chun et al.'s (2016) negative productivity effect might even amplify this effect, if the non-offshoring firms would suffer productivity losses as a consequence. This paper only considers offshoring and outsourcing in the case that the abroad-located operations are structured within the firm. Nevertheless, it is quite possible that a significant outsourcing and offshoring effect impacting stock returns positively could be found in a wide-enough sample. In this paper, however, the results aren't significant.

4.2. Limitations

In addition to numerical methods, we can assess the results' robustness through analysing the sample qualitatively. The main limitation of the sample and the results is certainly the low sample size. While there are several Nordic manufacturing firms especially in the paper and pulp sector, the industry is quite small in total for obtaining large-enough samples for meaningful results. This brought up the need to include other neighbouring countries in the sample – enter Germany. The German data widens the sample and makes the main results more robust, while perhaps diluting any Nordic-specific findings.

While initially planned to be included, there are relatively few manufacturing companies in Norway and Denmark fitting the sample criteria, so these countries were left out in the end. These countries do not have the forestry resources of their neighbouring Sweden and Finland, and this reflects to the relative lack of listed manufacturing firms in Oslo and Copenhagen.

The three countries chosen to the sample have some differences between one another. The German economy is, of course, several times larger than those of Sweden and Finland. Sweden's large set of listed finance stocks stands out, while Finland has a relatively low amount of both manufacturing and finance listed stocks. The country-level analysis shows that, while there are many differences, the results are broadly similar from one country to another. After all, all of these countries belong to the European Single Market, and their companies operate under broadly similar rules and regulations. Still, the analysis would benefit from having a wider sample to make the results more robust, and this might help in finding the effect described in the second hypothesis.

4.3. Conclusion

In conclusion, the simple linear model provides a well-fitting model for explaining manufacturing returns. Unit labour costs are found to explain manufacturing returns significantly and inversely, but the same, weaker but significant, effect can also be found in finance data from the same countries, from the same time period. In addition, while providing indications, this paper's results cannot show a significant effect, where offshoring firms would exhibit higher returns than domestic counterparts.

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Appendices

Appendix 1: List of stocks in manufacturing sample. "Domestic" firms underlined.

Componenta	Ahlstrom-Munksjö	Aumann AG	Traton
Kemira	Outokumpu	Schaltbau AG	Troax Group
Metsä Group	Stora Enso	Fortec Elektronik	Volvo
SSAB	UPM	Intica Systems	FM Mattsson Mora
Ponsse	Huhtamäki	KION Group AG	GARO
Kesla	Raute	SMT Scharf AG	Malmbergs Elektriska
Uutechnic Group	Valmet	DMG Mori	Momentum Group
Tulikivi	Cargotec	Dürr AG	Railcare Group
Dr. Hönle AG	Enedo	Krones AG	Svedbergs
Jenoptik	Elecster	KUKA AG	STS Group AG
LPKF Laser&Electr.	Exel Composites	SAF Holland	BMW
Singulus Tech.	Glaston	Stabilus AG	Volkswagen AG
SLM Solutions Group	KONE	Wacker Neuson	Daimler AG
Akasol AG	Konecranes	WashTec	Airbus
Bertrand AG	Metso Outotec	Knorr-Bremse	MTU Aero Engines
EDAG Engineering	Robit	SCA	OEM International
Paragon GmbH	Uponor	Hexpol	SAAB
SMT Scharf	Vaisala	ABB	Sandvik
Deutz AG	Valoe	Alfa Laval	SinterCast
Francotyp-Postalia	Wärtsilä	Alimak Group	SKF
Heidelberg Druck.	Nokian Tyres	AQ Group	Systemair
Jungheinrich	Basler	Assa Abloy	
Koenig & Bauer	Manz AG	Atlas Copco	
Rheinmetall AG	Pfeiffer Vacuum	Balco Group	
Elringklinger	PVA TePla AG	Beijer Alma	
DATA-MODUL AG	Varta AG	Cavotec	
Arctic Paper	Technotrans	Concentric	
BE Group	Viscom	Duroc	
Bergs Timber	Voltabox AG	Epiroc	
BillerudKorsnäs	Continental AG	Hanza Holding	
Holmen	Grammer AG	Inwido	
Profilgruppen	Hella	Lindab	
Rottneros	JOST Werke AG	Mycronic	
CTT Systems	LEONI AG	Nederman	
Fagerhult	Progress-werk	NIBE Industrier	
Fingerprint Cards	Schaeffler AG	Nolato	

Appendix 2: List of stocks in finance sample.

CAPSENSIXXaG	Fastpartnera	Fabege
CREDITSHELFaG	Havsfrun Investmentb	
ENCAVISaG	HEBAb	
FERRATUM OYJ	Hemblab	
GRENKEaG	Hemfosa Fastigheter	
HYPOPORTaG	Hoist Finance	
KAPaG	Hufvudstadena	
MLP SE	Industrivärdena	
OVB HOLDINGaG	Intrum	
SIXT LEASING O.N.	Investora	
COMMERZBANKaG	JM	
DEUTSCHEbANKaG NA O.N.	John Mattson Fastighetsföret.	
DT.PFANDBRIEFBKaG	K2A Knaust &anderssonb	
PROCREDIT HLDGaG NA EO 5	K-Fast Holdingb	
ALLIANZ SE VNA O.N.	Kinnevika	
Aktia Pankki	Klöverna	
Enento Group	Kungsleden	
CapMan	Latourb	
eQ	Lundbergföretagenb	
Evli Pankki	Magnoliabostad	
Oma Säästöpankki	Midwaya	
Taaleri	NAXS	
Ålandsbanken	NGS Group	
EAB Group	NP3 Fastigheter	
Panostaja	Nyfosa	
Sievi Capital	Öresund	
Unitedbankers	Oscar Properties Holding	
Nordea	Pandoxb	
Sampo	Platzer Fastigheter Holdingb	
Atrium Ljungbergb	Ratosa	
Avanzabank Holding	Resurs Holding	
Besqab	Sagaxa	
Bonavaa	Samhällsbyggnadsbo. i Nordenb	
Brinova Fastigheterb	SEBa	
Bure Equity	SSM Holding	
Castellum	Stendörren Fastigheterb	
Catellaa	Sv. Handelsbankena	
Catena	Svoldera	
Collector	Swedbanka	
Corem Property Groupa	TFbank	
Creadesa	Tractionb	
Diös Fastigheter	Wallenstamb	
Eastnine	Wihlborgs Fastigheter	